



A NOVEL OPTIMIZED FRAMEWORK FOR CARBOHYDRATE ESTIMATION FOR TYPE-1 PATIENTS USING MACHINE LEARNING

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ABSTRACT

Several deep learning (DL) depend forecasting approaches have been designed to estimate the carbohydrate level of type-1 diabetic patients accurately. Anyhow, they face some problems in execution. Thus, a novel integrated dove swarm algorithm with a recurrent neural network (DbRNM) model was proposed in this current work to estimate the carbohydrate level of type-1 diabetic patients. The developed approach was validated with the type-1 patient's dataset. Integrating the recurrent neural model eliminates the noisy content present in the database. Furthermore, the useful contents are taken out and computed to the system in the feature extraction module. And then, the type-1 patient is sorted depending on their carbohydrate level and categorized as low, high, and average. Additionally, a case study was designed to elaborate on the performance of the developed technique. The proposed model was implemented in python architecture, and working parameters were evaluated. In addition, a comparison assessment was conducted to validate that the presented model gained good final results compared than other convolutional models.

Keywords: Carbohydrate level, recurrent neural model, dove swarm algorithm, type-1 patients.

1. INTRODUCTION

Diabetes is a kind of chronic metabolic disease, and approximately 10% of people have type-1 diabetes worldwide [1]. In order to prevent type 1 diabetes, the blood glucose level is maintained close to normal for safety [2]. It encloses the capability of each to produce insulin because of the autoimmune destruction of pancreatic β -cells [3]. Patients with type-1 diabetes need exogenous insulin to control blood glucose. Insulin should be corrected and regulated otherwise, and patients can experience hypoglycaemia [4]. Type-1 diabetes is related to the long time complications such as neurological, microvascular and macrovascular [5]. Carbohydrate estimation is the most basic level which involves measuring the number of grams of carbohydrates in day-to-day meals [6]. Thus, measuring the carbohydrate amount is recommended for people with type-1 diabetes [7]. Carbohydrates give nearly 45% to 60% of our daily calories. The person with type 1 diseases levels from 150 grams to 250 grams of carbohydrate throughout the meal in the day [8, 9]. Type 1 diseases can be medicated with several insulin injections [10]. The meals as well as snacks allow child and adolescents to control their Type-1 Diabetes more efficiently within the daily routine [11]. Adolescents with Type-1 diabetes may positively affect [12] metabolism and reduce hypoglycemia events; anyhow, more high-quality medications are required to examine this positive effect [13].

Carbohydrates estimation is very challenging task since miscalculation of 20 grams can even impair the management of blood insulin [14]. So, the carbohydrate estimation should be more précised. In order for the people with type 1 disorder, carbohydrate estimation effectively manage their blood sugar levels [15]. Phenol-sulfuric acid is a calorimetric method to estimate the total concentration of carbohydrates in our food. Carbohydrates are of three types [16]. They are starch, sugar and fibre. Though carbohydrate is one of the greatest stimulants of the production of insulin, it create stop intake the carbohydrate food. Type-1 diabetic people with a greater carbohydrate diet can promote insulin prohibition [17].

With the advancement of DL algorithms, the classification of plant disease by leaf dataset is possible. Several scholars have already proposed several techniques for disease prediction, like convolutional neural networks (CNN) [18], recurrent neural networks (RNN) [19], and dilated recurrent neural networks (DRNN) [20]. Some limitations must be solved to evaluate the carbohydrate level of type-1 patients. It aims to develop an efficient DL-based approach for the carbohydrate level of type-1 diabetic patients.

The research work is arranged as follows; the recent related research papers that depend on carbohydrate prediction for type-1 patients are elaborated on in section 2. The problems present in predicting the carbohydrate level for patients are elaborated on in section 3. The proposed method for carbohydrate evaluation for patients is described in section 4. The outcomes of the presented approach and comparative analysis are described in section 5. And finally, this research paper ended with the conclusion in section 6.

2. RELATED WORK

A few recent related research papers relied on carbohydrate estimation for type-1 diabetic patients are described below,

John Martinsson *et al.* [19] proposed a technique that depends on the RNN, which only requires the glucose level of the patients. To estimate the efficiency of this model, the Ohio T1DM dataset was considered to forecast the blood glucose rate. This model attained lower root mean square error (RMSE) and surveillance error grid. And also, these metrics are compared with other convolutional models to show the superiority of this approach. Nevertheless, it has an insufficient training dataset.

In order to give 30 minutes predicts future glucose levels, Taiyu Zhu *et al.* [20] proposed a DL-dependent DRNN. With the utilization of dilation, this approach attains a highly receptive sector. Ohio T1DM dataset is utilized to predict the glucose rate of type-1 patients. The performance parameter gained lower error values, such as RMSE. It shows the effectiveness of the proposed model. Nevertheless, it needs high computational time to process the dataset.

Saiti, Kyriaki, *et al.* [21] integrate the linear, boosting, and bagging metaregression models to forecast the 30 minutes, 45 minutes, and 60 minutes forecast horizon. Compared with individual technique's results, the ensemble approach provides more accurate outcomes like glucose concentration and lower error values like RMSE and Clarke error grid assessment. But, it is a low prediction rate in the early stage.

To increase the strength and accuracy level of the haemoglobin A1C using the blood glucose level, Zaitcev, Aleksandr, *et al.* [22] presented a novel data-driven model relied on DL and CNN. This technique focuses on extracting characteristics from sequences of self-calculated blood glucose levels on different regular ranges. This model attained the performance matrices like reasonable mean and median absolute error. This model significantly enhances the

accuracy of the prediction. Yet, the process is expensive.

Güemes, Amparo, *et al.* [23] presented state of an art data-driven technique to forecast the grade of overnight glycaemic manages in type-1 diabetic patients. This approach predicts the overnight blood glucose level. This model attains better area under curve value. Also, this technique achieves a better classification accuracy rate when compared with traditional models. Anyhow, it needs a large amount of dataset.

The key contribution of the research work is elaborated below,

- At first, the type-1 diabetic patient's database is collected from the kaggle website and fed to the system model.
- Subsequently, a new hybrid DbRNM is developed with necessary forecasting and assessment features.
- The imported dataset was pre-processed in the hidden layer to remove the noisy contents.
- Then, the errorless features in the database were assessed and taken out in the classification phase, and the diabetic patient's carbohydrate level was calculated.
- At last, the performance of the designed system is assessed using evaluating the parameters related to precision, error level, recall, accuracy, and f-score.

3. SYSTEM MODEL WITH PROBLEM DESCRIPTION

Diabetes affects almost five hundred million people all over the world. So, estimating and maintaining the blood sugar level is necessary. Carbohydrates can directly affect the blood sugar level. With the development of AI, several ML-based techniques were designed to estimate and maintain the carbohydrate level of type-1 diabetic patients. Anyhow, those techniques enhance the complex class and cost. Furthermore, in the case of an unstructured dataset, the performance of those system models is lower. In fig.1 system model with the problem is illustrated.

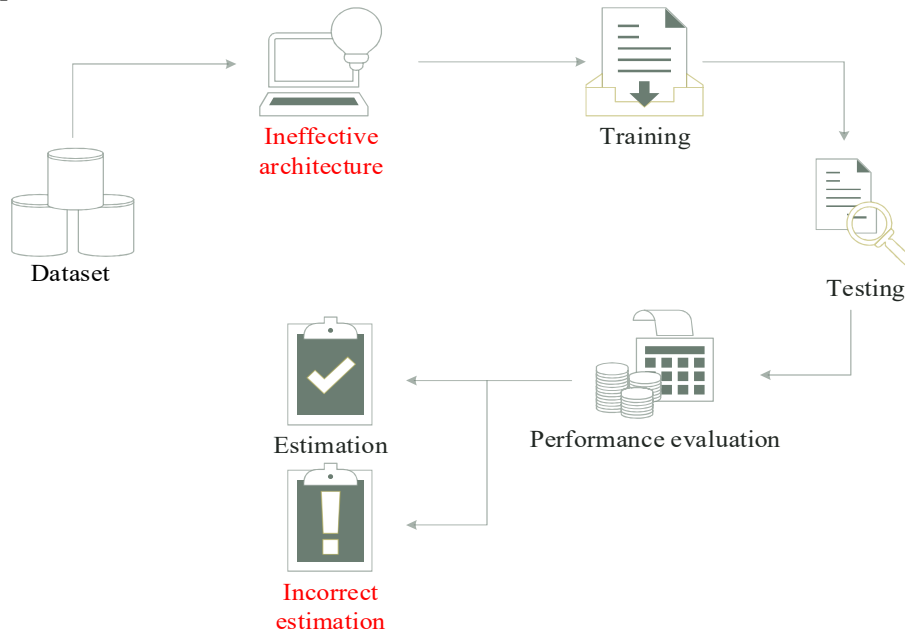


Fig.1 System model with problem

The problems from the existing works have high error rates, low accuracy rates and high

execution time while processing the dataset. The present work aims to develop a novel optimized method to estimate and maintain the carbohydrate level of type-1 diabetic patients from the trained database to tackle these problems.

4. PROPOSED METHODOLOGY

A novel dual dove swarm-based recurrent neural model (DbRNM) has been executed in this current study to estimate and maintain the carbohydrate level of type-1 diabetic patients. The designed method integrates the attributes of the dove swarm algorithm [24] and recurrent neural model [25]. Initially, the carbohydrate level data related to type-1 diabetic patients is collected from the kaggle website and fed to the PYTHON architecture. And then, the database was pre-processed in the hidden module to remove the unnecessary noisy contents.

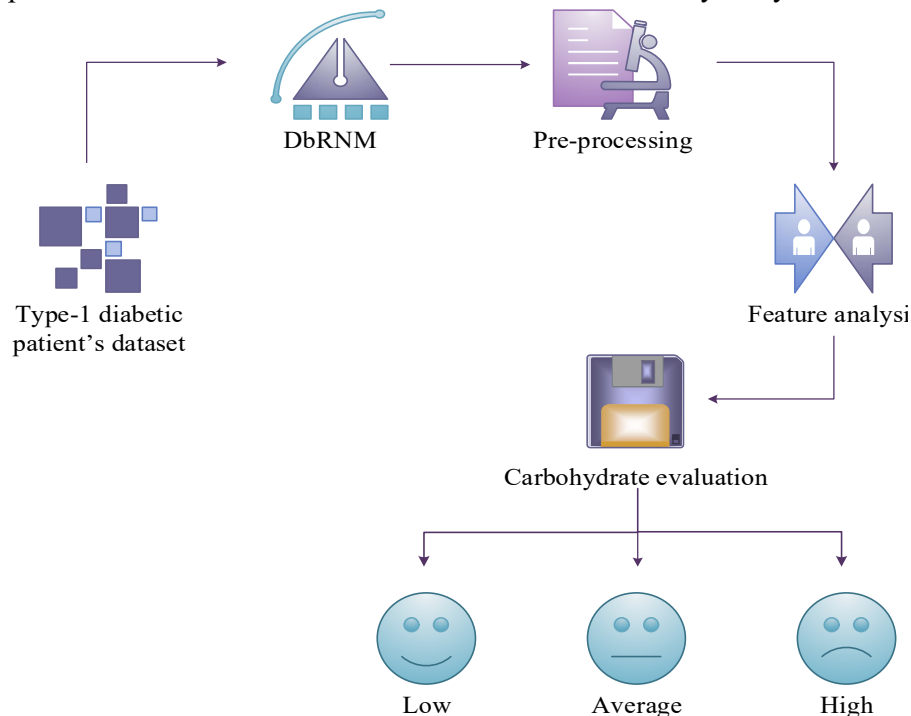


Fig.2 DbRNM framework

The present contents in the dataset are also identified and taken out in the feature analysis phase. The output of the feature analysis module is trained in the system to categorize the carbohydrate level of type-1 diabetic patients. At last, the carbohydrate level of type-1 diabetic patients has been recorded depending upon the range in the computed database. Furthermore, the performance matrices of the proposed technique have been verified and compared with existing methods. The presented model framework is represented in fig.2.

4.1. Design DbRNM model

DbRNM method consists of five phases: input, pre-processing, classification, optimal, and output. The input type-1 patient's carbohydrate level database is fed and initiated into the input phase. In the 2nd phase, the hidden phase, the imported database, is pre-processed to neglect the error/null and noisy content present in the dataset. The carbohydrate level of the type-1 patients is aligned in the classification phase. In fig.3, the layers of the developed DbRNM model are illustrated.

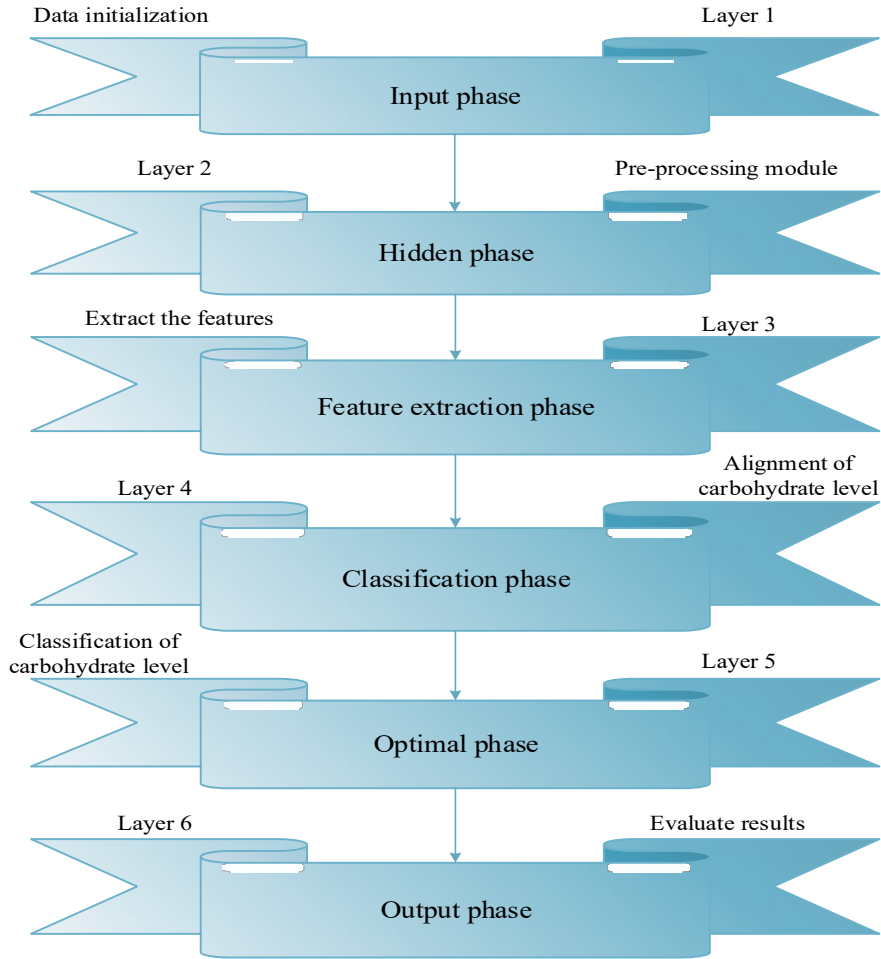


Fig.3. Layers of DbRNM

The type-1 diabetic patient's carbohydrate level is detected in the optimal module as low, average, and high. At last, the outcomes of the presented model are evaluated as the error value, f-measure, accuracy rate, recall and precision in the output module.

4.1.1. Pre-processing module

At first, the type-1 diabetic patient's database was gathered from kaggle websites and fed to the system model. This database contains details about the carbohydrate level of every patient. Then, the initiated database is initiated within the system model. The database initiation is given in Eqn. (1).

$$F(P_d) = (a_1, a_2, a_3, \dots, a_n) \quad (1)$$

Here F is the database initiation function, P_d indicates the patient's dataset, a denotes the data holds in the database and n represents the total number of data present in the database. And then, the imported database is pre-processed in the hidden module to enhance the accuracy of the categorization, as the null features are eliminated from the database. The pre-processing of the database is given in Eqn. (2).

$$\mathcal{P}(P_d) = P_d + \eta_o (P_d - \delta) \quad (2)$$

Here, \mathcal{P} indicates the function of pre-processing, η_o denotes the variable of noise removal and δ represents the noisy data held in the database. Hence, the noisy features is eliminated from

the database.

4.1.2. Feature extraction module

The pre-processed database enters to the feature analysis phase. The pre-processed database contains both meaningless as well as meaningful content. In this phase, the useful contents are taken out, and useless contents are removed. The feature extraction of the dataset is given in Eqn. (3).

$$\xi(P_{d(t,t^*)}) = \sum_{i=1}^n (P_d(t) - P_d(t^*)) \quad (3)$$

Here, ξ indicates the variable of feature extraction, t , and t^* represent the meaningful and useless contents in the database. Hence, the present meaningful parts are identified and taken out in the feature analysis phase.

4.1.3. Carbohydrate level detection

The extracted features hold the carbohydrate level of every type-1 patient. At first, the threshold value for every patient is evaluated, and then the lowest threshold score is place to record the number of patients beneath every level class. The threshold score evaluation is given in Eqn. (4).

$$S_v^* = \frac{S_f(cl)}{T} \quad (4)$$

Here, S_v^* signifies the threshold score evaluated to discover the mean carbohydrate level of every patient, S_f signifies the sum function, cl represents the maximum carbohydrate level of every type-1 patient, and T denotes the number of patients. Furthermore, the threshold score is placeto record the number of patients beneath various classes. It is represented in Eqn. (5).

$$R_f(S_v^*, t_{-} S_v^*) = \begin{cases} \text{If}(S_v^* < t_{-} S_v^*) & ; \text{count}(S_v^*) \\ R_f = \text{count}(S_v^*) \end{cases} \quad (5)$$

Here, R_f denotes the function and $t_{-} S_v^*$ represents the support value. In order to record the number of patients in every class, the support score is place as 80 and 180 (below 80, between 80 and 180, and higher than 180). Additionally, the patient's carbohydrate level was tracked in three classes: low, average and high. It is represented in Eqn. (6).

$$T_v = \begin{cases} S_v^* < 80 & ; \text{Low} \\ 80 > S_v^* < 180 & ; \text{Average} \\ S_v^* > 180 & ; \text{High} \end{cases} \quad (6)$$

Here, T_v signifies the detection variable. If the carbohydrate level of the type-1 patient is lower than 80, then the patient is categorized as low. If the carbohydrate level of the type-1 patient is between 80 and 180, then the patient is categorized as average. Subsequently, if the carbohydrate level of the type-1 patient is greater than 180, the patient is categorized as high.

Algorithm:1 DbRNM**begin**

{

Int $\rightarrow P_d = (c_1, c_2, c_3, \dots, c_n)$

//initialize the patient's dataset

Pre-processing phase()

{

int $\rightarrow \mathcal{G}$;

// initialize the pre-processing variables

 $\mathcal{G}(P_d) \rightarrow P_d - \delta$

// In the pre-processing module, the noisy data are eliminated

}

Feature_ Extraction()

{

int $\rightarrow \xi, \eta_0$;

// initialize the feature analysis variables

 $\xi(P_d) \rightarrow P_d(t - t^*)$

// The present features are traced, and meaningless contents are eliminated from database

}

Carbohydrate level_ detection ()

{

int $\rightarrow S_v^*, R_f$;

//initialization of threshold value variable to evaluate the average carbohydrate level of each patient

 $S_v^* \rightarrow S_f(c1)$ // S_f is the function of the average carbohydrate level of each patient $R_f \rightarrow \text{if}(S_v^* < t - S_v^*) \rightarrow \text{count}(S_v^*)$

// counting the number of patients whose average value is lower than the support value. Here, the lower threshold value is set in three various categories 80, 80-180, and 180.

 $\text{if}(S_v^* < 80)$

{

Low;

//If a patient's carbohydrate level is lower than 80, it is detected as "low."

}

 $\text{if}(80 > S_v^* < 180)$

{

Average;

//if a patient's carbohydrate level is between 80 and 180, it is detected as "average."

```

}
if( $S_v^* > 180$ )
{
High;
//If a patient's carbohydrate level is higher than 180, it is detected as "high."
}
}
}
stop

```

In addition, the workflow is elaborated in the format of pseudocode in algorithm 1. Hence, the system model detects the patient's carbohydrate level as average, low, or high.

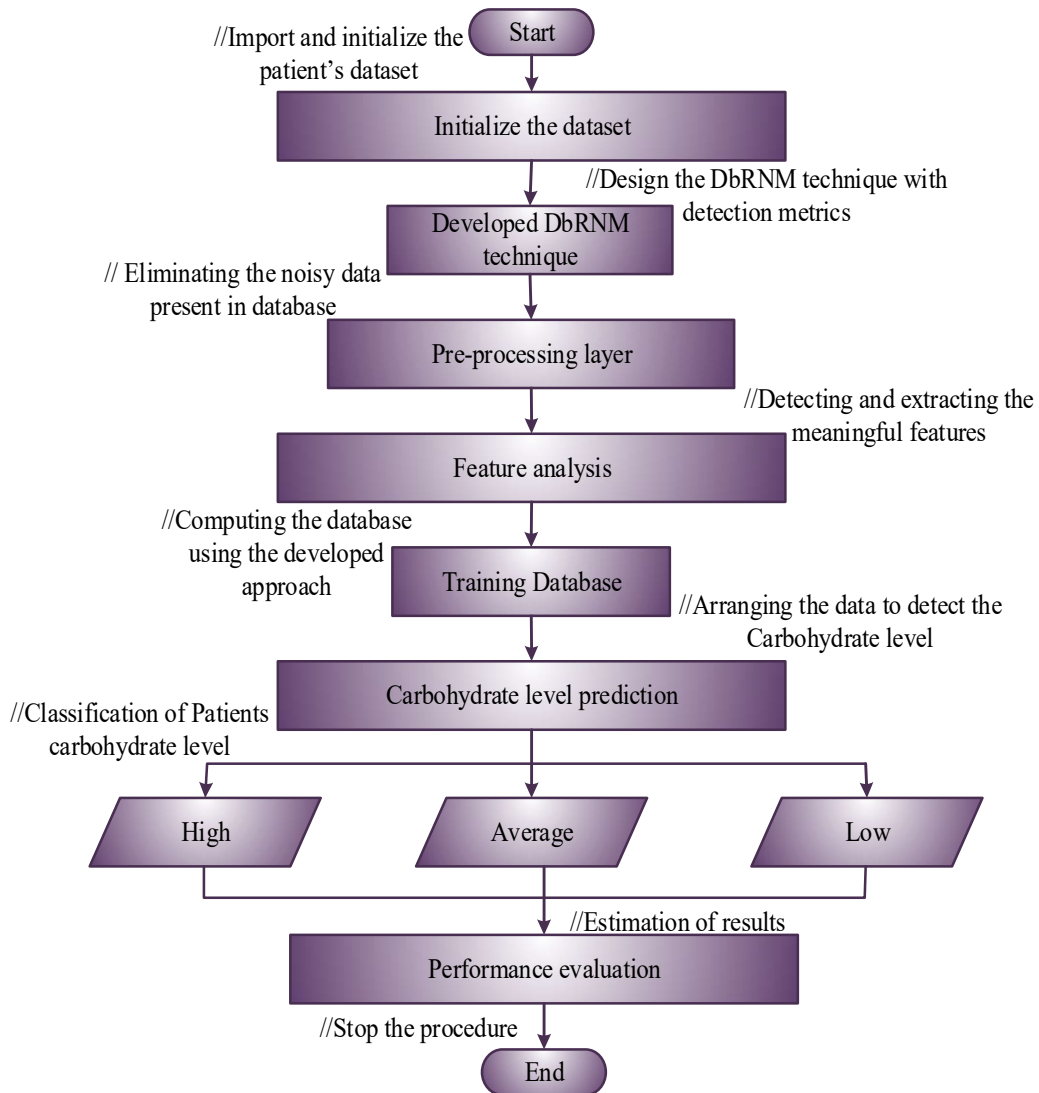


Fig.4 Workflow of DbRNM

The flowchart of the developed DbRNM approach is illustrated in fig.4. After performance

detection, the parameters such as f-measure, recall, accuracy, and precision.

5. RESULTS AND DISCUSSION

The current paper utilized a dual model to estimate and maintain the carbohydrate level of type-1 diabetic patients. The Carbohydrate level of type-1 diabetic patient's database was gathered and fed to the system model to verify the presented approach. Hybrid the dove swarm algorithm with a recurrent neural model helps to solve the average level and evaluates the type-1 patients in everyclass. The developed method has been executed in the PYTHON architecture, and the performance parameters are estimated.

Table.1 Execution parameters

Parameter	Specification
Platform	Python
Operating system	Windows 10
version	3.8
Data	Type-1 diabetic patient dataset

In the table.1, the description of the specification matrices is elaborated. At last, the performance of the developed method is verified using comparison of the outcomes with other existing DL-based models.

5.1 Case Study

To estimate the proposed model, a case study was carried out. The type-1 diabetic patient's database was gathered from the kaggle website to verify the developed technique. The imported database consists of gender, age, and carbohydrate level. The gathered database is initialized to the system and imported using the recurrent neural model. After importing, in the hidden layer, pre-processing was conducted on the imported database to remove the noisy contents in the database. Additionally, in the feature extraction phase, extracts meaningful features from the imported dataset. Then, the extracted feature contents are computed using the proposed methodology to categorize the carbohydrate level of the patients. In the proposed technique, the average carbohydrate level of every patient is evaluated by the function of threshold value. And then, the number of patients was specified by setting the threshold score as 80 as well as 180. If the support score is 80, the patients whose carbohydrate level is below 80 are measured and also extracted. Hereafter the database consists of the patients whose carbohydrate level is more than 80. While setting the support score as 180, the patients whose carbohydrate level is more than 80 and less than 180 are counted. In this procedure, the patients whose carbohydrate level is more than 180 are calculated separately. And now, there are three classes in the imported dataset.

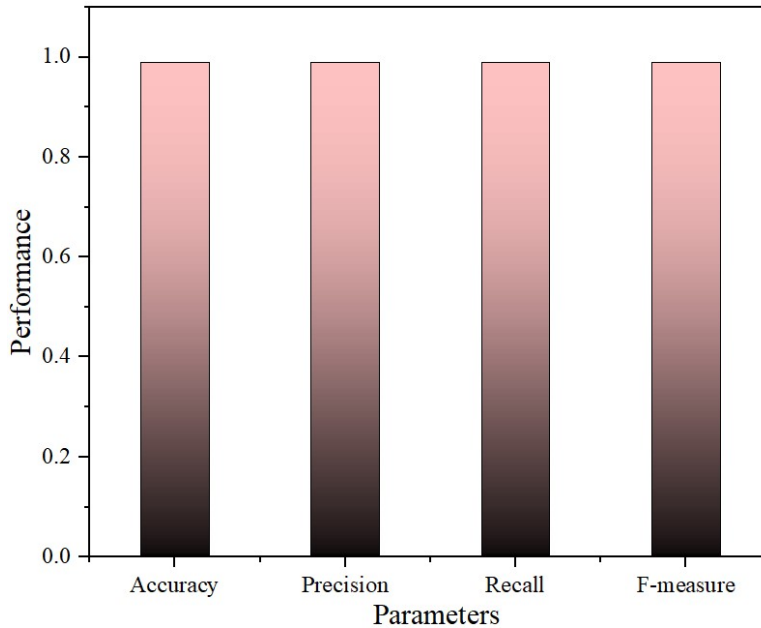


Fig.5. Performance of the DbRNM technique

The patients whose carbohydrate level is greater than 180 are noted as high, carbohydrate level between 80 and 180 is denoted as average, and the patients whose carbohydrate level is lower than 80 are specified as low. The carbohydrate level category of 250 type-1 patients is illustrated in fig.5. Finally, the designed method's performance is verified by evaluating the parameters such as error value, recall, accuracy, f-score, and precision.

5.2 Comparative Assessment

The proposed technique's efficiency is validated using the comparative analysis of various matrices such as exactness rate, precision value, recall level and f-score with other novel convolutional models. Existing techniques such as Deep Learning (DL) [26], Naive Bayes (NB) [26], Decision Tree (DT) [26], and Artificial Neural Network (ANN) [26] are used in the comparison process.

5.2.1 Accuracy level

The accuracy rate of the investigation varies between the prediction rate and the actual rate. To estimate the exactness level of the presented technique, the following Eqn.(7) is used

$$A_1^*(\%) = \frac{T.P^* + T.N^*}{T.P^* + F.P^* + T.N^* + F.N^*} \quad (7)$$

Where, A_1^* indicates the exactness level, $T.P^*$, and $F.P^*$ signify the true positive and false positive, respectively. $T.N^*$ and $F.N^*$ indicate the true negative and false negative, respectively.

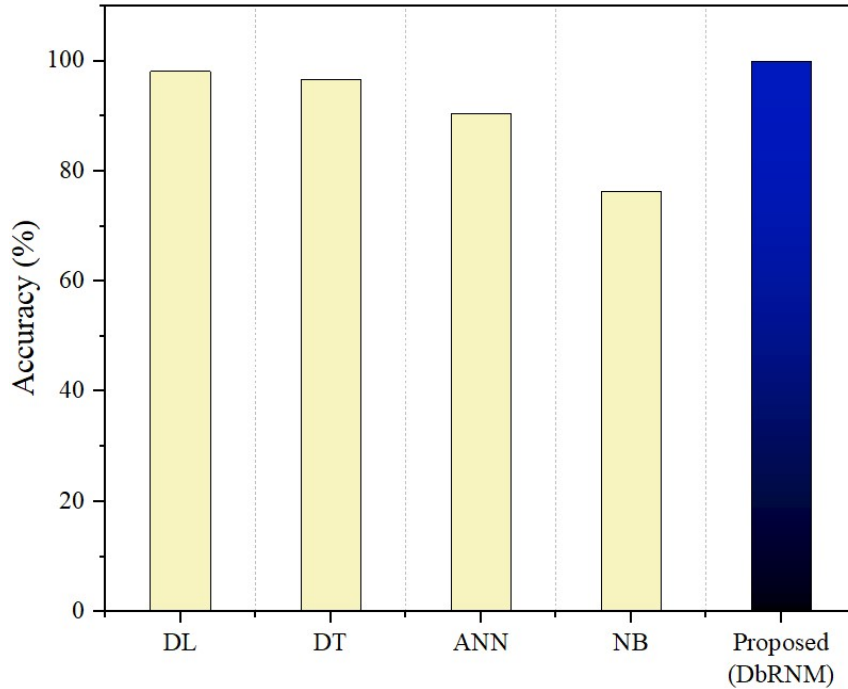


Fig.6. comparison of exactness

The accuracy level obtained using the developed technique is compared to other conventional models to validate the prediction rate is high in the designed replica. The accuracy level is compared to other models such as DL, DT, ANN, and NB. The exactness range of other replicas is 98.07%, 96.62%, 90.34%, and 76.33%. Yet, the proposed model achieved a high accuracy level of 99.94%. The comparison of exactness is represented in fig.6. It demonstrates that the developed model reached a better accuracy than other prediction techniques.

5.2.2 Precision rate

The precision level of the estimation and maintenance of the carbohydrate level of type-1 patients' architecture estimates the possibility of predicting the carbohydrate level with an actual carbohydrate level using the developed technique. The precision level of the developed model is evaluated using the following Eqn. (8).

$$P_1^* (\%) = \frac{T.P^*}{T.P^* + F.P^*} \quad (8)$$

Here, P_1^* indicates the precision level.

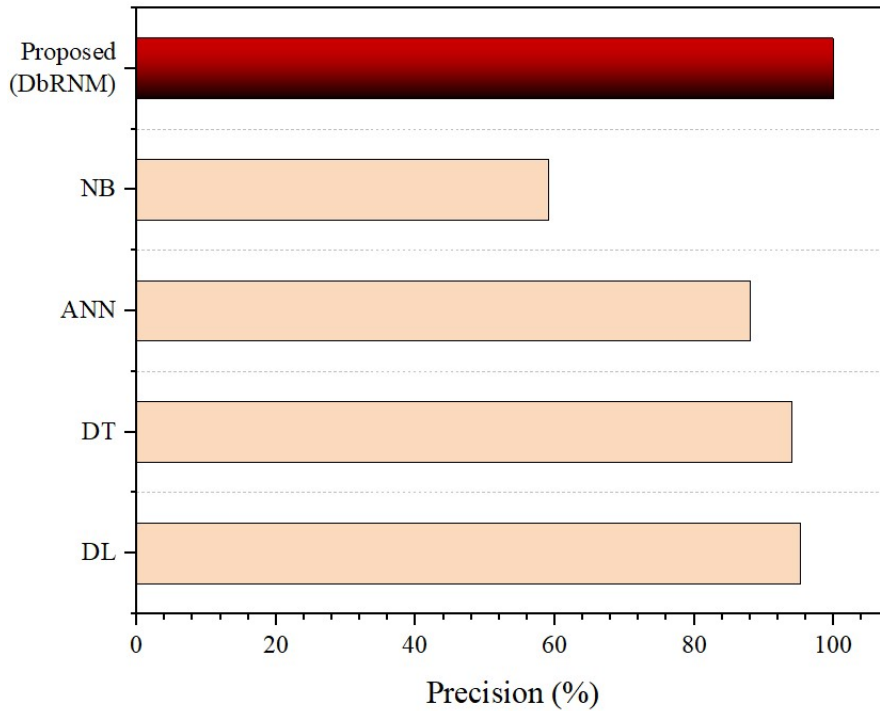


Fig.7. comparison of precision level

The precision level of the presented approach is compared with the other replicas, such as DL, DT, ANN, and NB. The precision level obtained by other conventional models is 95.22%, 94.02%, 88.05%, and 59.07%. Yet, the developed novel replica acquired a larger precision rate of 99.94%. The comparison of precision level is represented in fig.7. It demonstrates the proposed model attained a high precision level among others.

5.2.3 Recall value

In the detection procedure, recall value estimates all accurate optimal predictions out of all positive prediction rates. It is evaluated using the following Eqn. (9).

$$R_1^*(\%) = \frac{T.P^*}{T.P^* + F.N^*} \quad (9)$$

Here, R_1^* denotes the recall value.

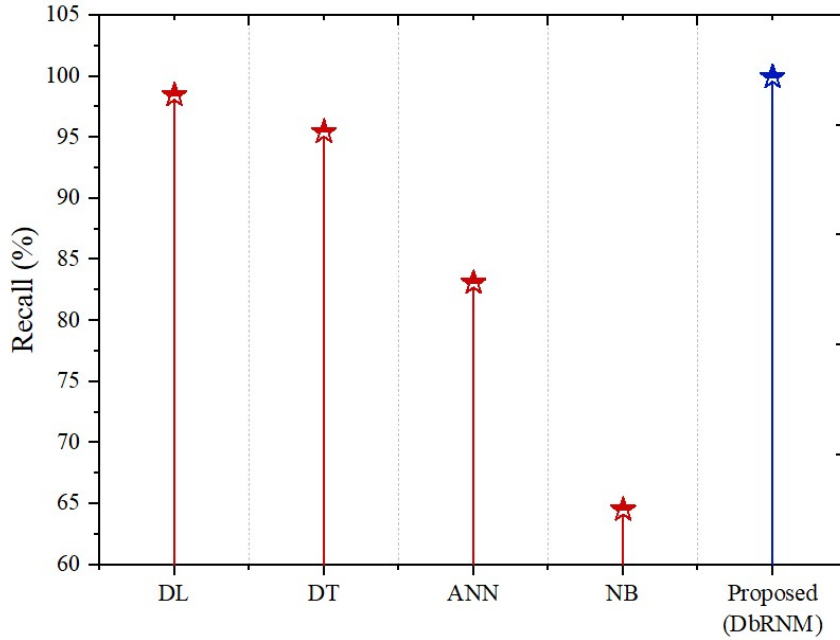


Fig.8. comparison of recall value

The recall value of the present technique is compared with other convolutional models such as DL, DT, ANN, and NB. The recall obtained using other models is 98.46%, 95.45%, 83.09%, and 64.51%. Yet, the proposed model received a high recall value of 99.94%. The comparison of recall value is represented in fig.8. It demonstrates that the developed method attained a higher recall value than others.

5.2.4 F-score

The f-score rate is exploited to estimate the binary system classifications. Generally, the f-score is utilized to evaluate the accurate level of the system's input data. It is evaluated using the parameters of precision level and recall value. It is estimated using the following Eqn. (10).

$$F_1^* (\%) = \frac{P_1^*}{R_1^*} (10)$$

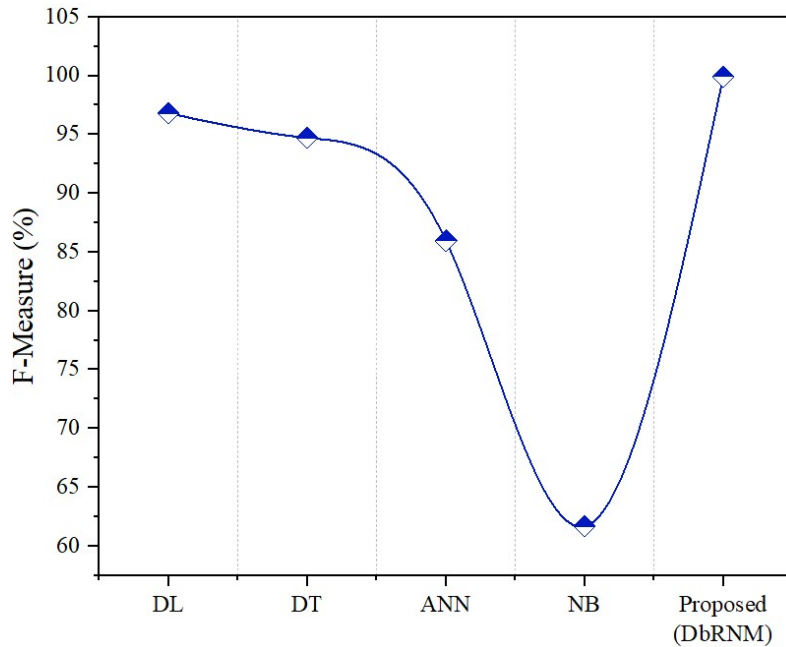


Fig. comparison of f-score

The f-score of the proposed model is compared to the other models, such as DL, DT, ANN, and NB. The f-score obtained by different models is 96.81%, 94.72%, 85.98%, and 61.67%. Yet, the proposed model gained a higher f-score of 99.94%. The comparison of the f-score is represented in fig.9. It validated that the developed model gained a high f-score compared to other convolutional models.

Table.2 Comparative analysis of various approaches

Parameters Methods	Exactness rate (%)	Precision level (%)	Recall value (%)	F-score (%)
DL	98.07	95.22	98.46	96.81
DT	96.62	94.02	95.45	94.72
ANN	90.34	88.05	83.09	85.98
NB	76.33	59.07	64.51	61.67
Proposed (DbRNM)	99.94	99.94	99.94	99.94

The overall comparison is elaborated on in the table.2. It validates that the presented DbRNM method achieved better performance when compared with other existing convolutional models. Hence, the developed DbRNM approach accurately estimates the carbohydrate level of type-1 patients.

5.3 Discussion

The proposed work's main motive is to evaluate each patient's carbohydrate level. The proposed model hybrid the dove swam algorithm with a recurrent neural approach. The type-1 patient's dataset was collected and imported into the python environment. The gathered database consists of the matrices such as gender, age, and carbohydrate level. Then it is initiated and pre-processed in the hidden module to eliminate the noisy content in the database. Furthermore, the meaningful contents are detected and extracted inside the feature analysis layer.

Table.3 Performance of DbRNM

<i>Parameter</i>	<i>Values</i>
Accuracy rate (%)	99.94
Precision level (%)	99.94
Recall value (%)	99.94
F-score (%)	99.94
Error value (%)	0.001

Then, the carbohydrate level of the patient is detected in three different classes: low, high, and average, depending on the support value. Furthermore, the number of patients in every category is also recorded. At last, the performance parameters concerning error level, recall, f-measure, precision, and accuracy are evaluated and compared with other existing convolutional models. The performance method indicates that the developed system gained a high accuracy level of 99.94%, a greater precision and recall value of 99.94% and 99.94%, a high f-measure of 99.94%, and the lowest error rate of 0.001%. In the table.3, the performance analysis of the presented technique is tabulated.

CONCLUSION

The current approach aims to estimate the carbohydrate level of type-1 patients as low, high, and average. The type-1 patient dataset was gathered and initiated within the system to verify the proposed method. At first, the database was pre-processed in the hidden phase, and the error-less data was fed into the next feature analysis phase. The extracted features were computed and utilized in the prediction process. The developed approach was executed in the python platform, and the outcomes were evaluated. In addition, a hybrid of the dove swarm optimization with the recurrent neural model enhances the performance of the system model to classify the patients. The final results of the proposed replica are compared with other existing convolutional methods to verify the effectiveness of the presented approach. A comparative assessment proved that the presented model attained the accuracy, precision level, recall value and f-score enhanced about 99.94%, 99.94%, 99.94%, and 99.94%. Additionally, the error value is minimized by 0.001%.

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